

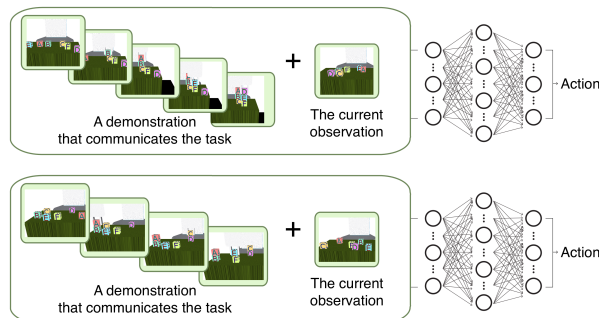
One-Shot Imitation Learning

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Abstract

Imitation learning has been commonly applied to solve different tasks in isolation. This usually requires either careful feature engineering, or a significant number of samples. This is far from what we desire: ideally, robots should be able to learn from very few demonstrations of any given task, and instantly generalize to new situations of the same task, without requiring task-specific engineering. In this paper, we propose a meta-learning framework for achieving such capability, which we call *one-shot imitation learning*.

Specifically, we consider the setting where there is a very large (maybe infinite) set of tasks, and each task has many instantiations. For example, a task could be to stack all blocks on a table into a single tower, another task could be to place all blocks on a table into two-block towers, etc. In each case, different instances of the task would consist of different sets of blocks with different initial states. At training time, our algorithm is presented with pairs of demonstrations for a subset of all tasks. A neural net is trained that takes as input one demonstration and the current state (which initially is the initial state of the other demonstration of the pair), and outputs an action with the goal that the resulting sequence of states and actions matches as closely as possible with the second demonstration. At test time, a demonstration of a single instance of a new task is presented, and the neural net is expected to perform well on new instances of this new task. Our experiments show that the use of soft attention allows the model to generalize to conditions and tasks unseen in the training data. We anticipate that by training this model on a much greater variety of tasks and settings, we will obtain a general system that can turn any demonstrations into robust policies that can accomplish an overwhelming variety of tasks.



One-shot policy. A single policy trained to solve many tasks.



(left) Task-specific policy. This policy is trained to stack blocks into two towers, each of height 3. (right) A separate task-specific policy. This policy is trained to stack blocks into three towers, each of height 2.

Figure 1. Traditionally, policies are task-specific. For example, a policy might have been trained (through imitation or reinforcement learning) to stack blocks into towers of height 3, and then another policy would be trained to stack blocks into towers of height 2, etc. In this paper, we are interested in policies that are *not* specific to one task, but rather can be told (through a single demonstration) what the current new task is, and be successful at this new task. As illustrative examples, we would want to be able to provide a single demonstration of each task, and from that the one-shot policy would know what to do when faced with a new situation of the task, where the blocks are randomly rearranged. Videos of the illustrated tasks are available at <http://bit.ly/one-shot-imitation>.

1. Introduction

We are interested in robotic systems that are able to perform a variety of complex useful tasks, e.g. tidying up a home or preparing a meal. The robot should be able to learn new tasks without long system interaction time. To accomplish this, we must solve two broad problems:

- The first problem is that of dexterity: robots should learn how to approach, grasp and pick up complex un-

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actuated objects, and how to place or arrange them into a desired configuration.

- The second problem is that of communication: how to communicate the *intent* of the task at hand, so that the robot can replicate it in a broader set of initial conditions.

Demonstrations are an extremely convenient form of information we can use to teach robots to overcome these two challenges. Using demonstrations, we can unambiguously communicate essentially any manipulation task, and simultaneously provide clues about the specific motor skills required to perform the task. We can compare this with an alternative form of communication, namely natural language. Although language is highly versatile, effective, and efficient, natural language processing systems are not yet at a level where we could easily use language to precisely describe a complex task to a robot. Compared to language, demonstration has two fundamental advantages: first, it does not require the knowledge of language, as it is possible to communicate complex tasks to humans that don't speak one's language. And second, there are many tasks that are extremely difficult to explain in words, even if we assume perfect linguistic abilities: for example, explaining how to swim without demonstration and experience seems to be, at the very least, an extremely challenging task.

However, so far imitation learning has not been a silver bullet. Practical applications of imitation learning have either required careful feature engineering, or a significant amount of system interaction time. This is far from what we desire: ideally, we hope to demonstrate a certain task only once or a few times to the robot, and have it instantly generalize to new situations of the same task, without long system interaction time or domain knowledge about individual tasks.

In this paper we explore the one-shot imitation learning setting, where the objective is to maximize the expected performance of the learned policy when faced with a new, previously unseen, task, and having received as input only one demonstration of that task. For the tasks we consider, the policy is expected to achieve good performance without any additional system interaction, once it has received the demonstration.

We train a policy on a broad distribution over tasks, where the number of tasks is potentially infinite. For each training task we assume the availability of a set of successful demonstrations. Our learned policy takes as input: (i) the current observation, and (ii) one demonstration that successfully solves a different instance of the same task (this demonstration is fixed for the duration of the episode). The policy outputs the current controls. We note that any pair of demonstrations for the same task provides a super-

vised training example for the neural net policy, where one demonstration is treated as the the input, while the other as the output.

To make this model work, we made essential use of soft attention (Bahdanau et al., 2014) for processing both the (potentially long) sequence of states and action that correspond to the demonstration, and for processing the components of the vector specifying the locations of the various blocks in our environment. The use of soft attention over both types of inputs made strong generalization possible. In particular, on the family of block stacking tasks shown in Fig. 1, our neural network policy was able to perform well on novel block configurations which were not present in any training data.

This approach, if scaled up appropriately by training on a very wide variety of tasks and demonstrations, is likely to successfully learn a model for communicating complex tasks to a robot that works well in many practical settings.

2. Related Work

Imitation learning considers the problem of acquiring skills from observing demonstrations. Survey articles include (Schaal, 1999; Calinon, 2009; Argall et al., 2009).

Two main lines of work within imitation learning are behavioral cloning, which performs supervised learning from observations to actions (e.g., Pomerleau (1989); Ross et al. (2011)); and inverse reinforcement learning (Ng & Russell, 2000), where a reward function (Abbeel & Ng, 2004; Ziebart et al., 2008; Levine et al., 2011; Finn et al., 2016; Ho & Ermon, 2016) is estimated that explains the demonstrations as (near) optimal behavior. While this past work has led to a wide range of impressive robotics results, it considers each skill separately, and having learned to imitate one skill does not accelerate learning to imitate the next skill.

One-shot and few-shot learning has been studied for image recognition (Vinyals et al., 2016; Koch, 2015; Santoro et al., 2016; Ravi & Larochelle, 2017), generative modeling (Edwards & Storkey, 2017; Rezende et al., 2016), learning “fast” reinforcement learning agents with recurrent policies (Duan et al., 2016; Wang et al., 2016). Fast adaptation has also been achieved through fast-weights (Ba et al., 2016). Like our algorithm, many of the aforementioned approaches are a form of meta-learning (Thrun & Pratt, 1998; Schmidhuber, 1987; Naik & Mammone, 1992), where the algorithm itself is being learned. Meta-learning has also been studied to discover neural network weight optimization algorithms (Bengio et al., 1992; Schmidhuber, 1992; Andrychowicz et al., 2016). This prior work on one-shot learning and meta-learning, however, is tailored to respective domains (image recognition, genera-

tive models, reinforcement learning, optimization) and not directly applicable in the imitation learning setting.

Reinforcement learning (Sutton & Barto, 1998; Bertsekas & Tsitsiklis, 1995) provides an alternative route to skill acquisition, by learning through trial and error. Reinforcement learning has had many successes, including Backgammon (Tesauro, 1995), helicopter control (Ng et al., 2003), Atari (Mnih et al., 2015), Go (Silver et al., 2016), continuous control in simulation (Schulman et al., 2015; Heess et al., 2015; Lillicrap et al., 2015) and on real robots (Peters & Schaal, 2008; Levine et al., 2016). However, reinforcement learning tends to require a large number of trials and requires specifying a reward function to define the task at hand. The former can be time-consuming and the latter can often be significantly more difficult than providing a demonstration (Ng & Russell, 2000).

Multi-task and transfer learning considers the problem of learning policies with applicability and re-use beyond a single task. Success stories include domain adaptation in computer vision (Yang et al., 2007; Kulis et al., 2011; Tzeng et al., 2014; Donahue et al., 2014) and control (Tzeng et al., 2015; Rusu et al., 2016; Sadeghi & Levine, 2016; Gupta et al., 2017; Stadie et al., 2017). However, while acquiring a multitude of skills faster than what it would take to acquire each of the skills independently, these approaches do not provide the ability to readily pick up a new skill from a single demonstration.

Our approach heavily relies on an attention model over the demonstration and an attention model over the current observation. We use the soft attention model proposed in (Bahdanau et al., 2014) for machine translations, and which has also been successful in image captioning (Xu et al., 2015). The interaction networks proposed in (Battaglia et al., 2016; Chang et al., 2017) also leverage locality of physical interaction in learning. Our model is also related to the sequence to sequence model (Sutskever et al., 2014; Cho et al., 2014), as in both cases we consume a very long demonstration sequence and, effectively, emit a long sequence of actions.

3. One Shot Imitation Learning

3.1. Problem Formalization

We denote a distribution of tasks by \mathbb{T} , an individual task by $t \sim \mathbb{T}$, and a distribution of demonstrations for the task t by $\mathbb{D}(t)$. A policy is symbolized by $\pi_\theta(a|o, d)$, where a is an action, o is an observation, d is a demonstration, and θ are the parameters of the policy. A demonstration $d \sim \mathbb{D}(t)$ is a sequence of observations and actions : $d = [(o_1, a_1), (o_2, a_2), \dots, (o_T, a_T)]$. We assume that the distribution of tasks \mathbb{T} is given, and that we can obtain successful demonstrations for each task in $t \in \mathbb{T}$. We assume

that there is some scalar-valued evaluation function $R_t(d)$ (e.g. a binary value indicating success) for each task, although this is not required during training. The objective is to maximize the expected performance of the policy, where the expectation is taken over tasks $t \in \mathbb{T}$, and demonstrations $d \in \mathbb{D}(t)$.

3.2. Example Settings

To clarify the problem setting, we describe two concrete examples, which we will also later study in the experiments.

3.2.1. PARTICLE REACHING

The particle reaching problem is a very simple family of tasks. In each task, we control a point robot to reach a specific landmark, and different tasks are identified by different landmarks. As illustrated in Fig. 2, one task could be to reach the orange square, and another task could be to reach the green triangle. The agent receives its own 2D location, as well as the 2D locations of each of the landmarks. Within each task, the initial position of the agent, as well as the positions of all the landmarks, can vary across different instances of the task.

Without a demonstration, the robot does not know which landmark it should reach, and will not be able to accomplish the task. Hence, this setting already gets at the essence of one-shot imitation, namely to communicate the task via a demonstration. After learning, the agent should be able to identify the target landmark from the demonstration, and reach the same landmark in a new instance of the task.

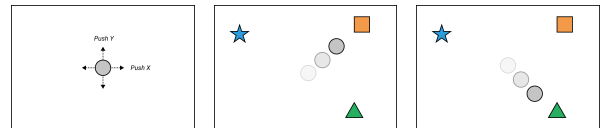


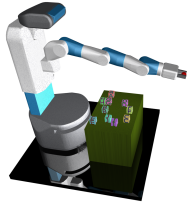
Figure 2. The robot is a point mass controlled with 2-dimensional force. The family of tasks is to reach a target landmark. The identity of the landmark differs from task to task, and the model has to figure out which target to pursue based on the demonstration. (left) illustration of the robot; (middle) the task is to reach the orange box, (right) the task is to reach the green triangle.

3.2.2. BLOCK STACKING

We now consider a more challenging set of tasks, which requires more advanced manipulation skills, and where different tasks share a compositional structure, which allows us to investigate nontrivial generalization to unseen tasks. In the block stacking tasks family, the goal is to control a 7-DOF Fetch robotic arm to stack various numbers of cube-

⁰<http://fetchrobotics.com/>

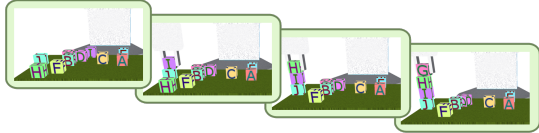
shaped blocks into configurations specified by the user. Each configuration consists of a list of blocks arranged into towers of different heights, and can be identified by a string such as `ghij` or `ab cd ef gh`, as illustrated in Fig. 3. Each of these configurations correspond to a different task. In a typical task, an observation is a list of (x, y, z) object positions relative to the gripper, and information if gripper is opened or closed. The number of objects may vary across different task instances.



An example of the initial state, where blocks are randomly placed on the table.



Trajectory of stacking 4 towers of height 2 each, where block A is on top of block B, block C is on top of block D, block E is on top of block F, and block G is on top of block H. This task is identified as `ab cd ef gh`.



Trajectory of stacking 1 block tower of height 4, where block G is on top of block H, block H is on top of block I, and block I is on top of block J. This task is identified as `ghij`.

Figure 3. The tasks are to control a Fetch robotic arm to stack blocks into various layouts. Entire episode takes up to several thousand time-steps. We define a *stage* as a single operation of stacking one block on top of another. The first task shown above has 4 stages, whereas the second task has 3.

3.3. Algorithm

In order to train the neural network policy, we can use any algorithms for policy learning in sequential decision making problems. For example, if rewards are available in the training tasks, we can use reinforcement learning to optimize the policy. The only modification required is to condition the policy on a randomly chosen demonstration at the beginning of each episode. In this paper, we focus on imitation learning algorithms such as behavioral cloning and DAGGER (Ross et al., 2011), which only require demon-

strations rather than reward functions to be specified.¹ This has the potential to be more scalable, since it is often easier to demonstrate a task than specifying a well-shaped reward function (Ng et al., 1999).

We start by collecting a set of demonstrations for each task, where we add noise to the actions in order to have wider coverage in the trajectory space. In each training iteration, we sample a list of tasks (with replacement). For each sampled task, we sample a demonstration as well as a small batch of observation-action pairs. The policy is trained to regress against the desired actions when conditioned on the current observation and the demonstration, by minimizing an ℓ_2 or cross-entropy loss based on whether actions are continuous or discrete. Across all experiments, we use Adamax (Kingma & Ba, 2014) to perform the optimization with a learning rate of 0.001.

4. Architectures

While, in principle, a generic neural network could learn the mapping from demonstration and current observation to appropriate action, we found it important to use an appropriate architecture. Our architecture for learning block stacking is one of the main contributions of this paper, and we believe it is representative of what architectures for one-shot imitation learning of more complex tasks could look like in the future. Although the particle task is simpler, we also found architectural decisions to be important, and we consider several choices below to be evaluated in Section 5.1.

4.1. Architecture for Particle Reaching

We consider three architectures for this problem:

- **Plain LSTM:** The first architecture is a simple LSTM (Hochreiter & Schmidhuber, 1997) with 512 hidden units. It reads the demonstration trajectory, the output of which is then concatenated with the current state, and fed to a multi-layer perceptron (MLP) to produce the action.
- **LSTM with attention:** In this architecture, the LSTM outputs a weighting over the different landmarks from the demonstration sequence. Then, it applies this weighting in the test scene, and produces a weighted combination over landmark positions given the current state. This 2D output is then concatenated with the current agent position, and fed to an MLP to produce the action.

¹To be more exact, DAGGER also requires interactive supervision during training.

- **Final state with attention:** Rather than looking at the entire demonstration trajectory, this architecture only looks at the final state in the demonstration (which is already sufficient to communicate the task), and produce a weighting over landmarks. It then proceeds like the previous architecture.

Notice that these three architectures are increasingly more specialized to the specific particle reaching setting, which suggests a potential trade-off between expressiveness and generalizability. We will quantify this tradeoff in Section 5.1.

4.2. Architecture for Block Stacking

For the block stacking task, it is desirable that the policy architecture has the following properties:

1. It should be easy to apply to task instances that have varying number of blocks.
2. It should naturally generalize to different permutations of the same task. For instance, the policy should perform well on task `dcba`, even if it is only trained on task `abcd`.
3. It should accommodate demonstrations of variable lengths.

Our proposed architecture consists of three modules: the demonstration network, the context network, and the manipulation network. The modules make essential use of a neighborhood attention operation. We will first describe this operation in more detail, followed by describing each of the three modules.

4.2.1. NEIGHBORHOOD ATTENTION

Since our neural network needs to handle demonstrations with variable numbers of blocks, it must have modules that can process variable-dimensional inputs. Soft attention is a natural operation which maps variable-dimensional inputs to fixed-dimensional outputs. However, by doing so, it may lose information compared to its input. This is undesirable, since the amount of information contained in a demonstration grows as the number of blocks increases. Therefore, we need an operation that can map variable-dimensional inputs to outputs with comparable dimensions. Intuitively, rather than having a single output as a result of attending to all inputs, we have as many outputs as inputs, and have each output attending to all other inputs in relation to its own corresponding input.

We start by describing the soft attention module as specified in (Bahdanau et al., 2014). The input to the attention includes a query q , a list of context vectors $\{c_j\}$, and a list

of memory vectors $\{m_j\}$. The i th attention weight is given by

$$w_i \leftarrow v^T \tanh(q + c_i) \quad (1)$$

where v is a learned weight vector. The output of attention is a weighted combination of the memory content, where the weights are given by a softmax operation over the attention weights. Formally, we have

$$\text{output} \leftarrow \sum_i m_i \frac{\exp(w_i)}{\sum_j \exp(w_j)} \quad (2)$$

Note that the output has the same dimension as a memory vector. The attention operation can be generalized to multiple query heads, in which case there will be as many output vectors as there are queries.

Now we turn to neighborhood attention. We assume there are B blocks in the environment. We denote the robot's state as s_{robot} (in the block stacking experiment, this only includes information about whether the gripper is open or closed), and the coordinates of each block as $(x_1, y_1, z_1), \dots, (x_B, y_B, z_B)$. The input to neighborhood attention is a list of embeddings $h_1^{\text{in}}, \dots, h_B^{\text{in}}$ of the same dimension, which can be the result of a projection operation over a list of block positions, or the output of a previous neighborhood attention operation. Given this list of embeddings, we use two separate linear layers to compute a query vector and a context embedding for each block:

$$\begin{aligned} q_i &\leftarrow \text{Linear}(h_i^{\text{in}}) \\ c_i &\leftarrow \text{Linear}(h_i^{\text{in}}) \end{aligned} \quad (3)$$

The memory content to be extracted consists of the coordinates of each block, concatenated with the input embedding. The i th query result is given by the following soft attention operation:

$$\begin{aligned} \text{result}_i &\leftarrow \text{SoftAttention}(\text{query} : q_i, \\ &\quad \text{context} : \{c_j\}_{j=1}^B, \\ &\quad \text{memory} : \{\text{concat}((x_j, y_j, z_j), h_j^{\text{in}}))\}_{j=1}^B) \end{aligned} \quad (4)$$

Intuitively, this operation allows each block to query other blocks in relation to itself (e.g. find the closest block), and extract the queried information. An illustration of the operation is shown in Fig. 4.

The gathered results are then combined with each block's own information, to produce the output embedding per block. Concretely, we have

$$\text{output}_i \leftarrow \text{Linear}(\text{concat}(h_i^{\text{in}}, \text{result}_i, (x_i, y_i, z_i), s_{\text{robot}})) \quad (5)$$

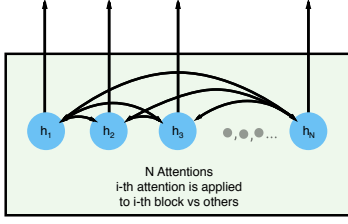


Figure 4. Illustration of the neighborhood attention operation. It receives a list of embeddings for each block, performs one attention query corresponding to each block, and outputs a list of embeddings which have the same dimension as the input.

In practice, we use multiple query heads per block, so that the size of each result_{*i*} will be proportional to the number of query heads.

4.2.2. DEMONSTRATION NETWORK

Illustrated in Fig. 5, the demonstration network receives a demonstration trajectory as input, and produces an embedding of the demonstration to be used by the policy. The size of this embedding grows linearly as a function of the length of the demonstration as well as the number of blocks in the environment.

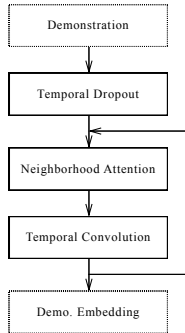


Figure 5. Demonstration network.

For block stacking, the demonstrations can span hundreds to thousands of time steps, and training with such long sequences can be demanding in both time and memory usage. Hence, we randomly discard a subset of time steps during training, an operation we call *temporal dropout*, analogous to (Srivastava et al., 2014; Krueger et al., 2016). We denote p as the proportion of time steps that are thrown away. In our experiments, we use $p = 0.95$, which reduces the length of demonstrations by a factor of 20. During test time, we can sample multiple downsampled trajectories, use each of them to compute downstream results, and average these results to produce an ensemble estimate. As shown in Section 5.2.3, this consistently improves the per-

formance of the policy.

After downsampling the demonstration, we apply a sequence of operations, composed of dilated temporal convolution (Yu & Koltun, 2016) and neighborhood attention.

4.2.3. CONTEXT NETWORK

The context network is the crux of our model. Illustrated in Fig. 6, it processes both the current state and the embedding produced by the demonstration network, and outputs a context embedding, whose dimension does not depend on the length of the demonstration, or the number of blocks in the environment. Hence, it is forced to capture only the relevant information, which will be used by the manipulation network.

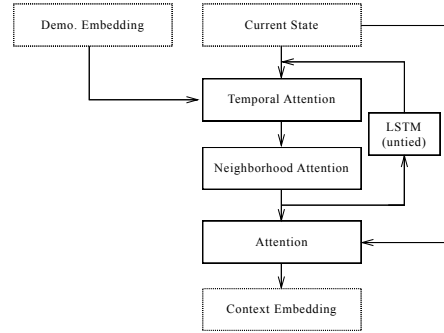


Figure 6. Context network.

The context network starts by computing a query vector as a function of the current state, which is then used to attend over the different time steps in the demonstration embedding. The attention weights over different blocks within the same time step are summed together, to produce a single weight per time step. The result of this temporal attention is a vector whose size is proportional to the number of blocks in the environment. We then apply neighborhood attention to propagate the information across the embeddings of each block. This process is repeated multiple times, where the state is advanced using an LSTM cell with untied weights.

The previous sequence of operations produces an embedding whose size is independent of the length of the demonstration, but still dependent on the number of blocks. We then apply standard soft attention to produce fixed-dimensional vectors, where the memory content only consists of positions of each block, which, together with the robot’s state, forms the input passed to the manipulation network.

Intuitively, although the number of objects in the environment may vary, at each stage of the manipulation operation, the number of relevant objects is small and usually fixed. For the block stacking environment specifically, the

robot should only need to pay attention to the position of the block it is trying to pick up (the *source* block), as well as the position of the block it is trying to place on top of (the *target* block). Therefore, a properly trained network can learn to match the current state with the corresponding stage in the demonstration, and infer the identities of the source and target blocks expressed as soft attention weights over different blocks, which are then used to extract the corresponding positions to be passed to the manipulation network. Although we do not enforce this interpretation in training, our experiment analysis supports this interpretation of how the learned policy works internally.

4.2.4. MANIPULATION NETWORK

The manipulation network is the simplest component. Illustrated in Fig. 7, after extracting the information of the source and target blocks, it computes the action needed to complete the current stage of stacking one block on top of another one, using a simple MLP network.² This division of labor opens up the possibility of modular training: the manipulation network may be trained to complete this simple procedure, without knowing about demonstrations or more than two blocks present in the environment. We leave this possibility for future work.

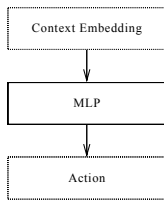


Figure 7. Manipulation network.

5. Experiments

5.1. Particle Reaching

To demonstrate the key concepts that underlie the one-shot imitation learning framework, we conduct experiments with the simple 2D particle reaching task described in Section 3.2.1. We consider an increasingly difficult set of task families, where the number of landmarks increases from 2 to 10. For each task family, we collect 10000 trajectories for training, where the positions of landmarks and the starting position of the point robot are randomized. We use a hard-coded expert policy to efficiently generate demonstrations. We add noise to the trajectories by perturbing the computed actions before applying them to the environment, and we use simple behavioral cloning to train the

²In principle, one can replace this module with an RNN module. But we did not find this necessary for the tasks we consider.

neural network policy. The trained policy is evaluated on new scenarios and conditioned on new demonstration trajectories unseen during training.

We evaluate the performance of the three architectures described in Section 4.1. For the LSTM-based architectures, we apply dropout (Srivastava et al., 2014) to the fully connected layers, by zeroing out activations with probability 0.1 during training.

5.1.1. RESULTS

The results are shown in Fig. 8. We observe that as the architecture becomes more specialized, we achieve much better generalization performance. For this simple task, it appears that conditioning on the entire demonstration hurts generalization performance, and conditioning on just the final state performs the best even without explicit regularization. This makes intuitive sense, since the final state already sufficiently characterizes the task at hand.

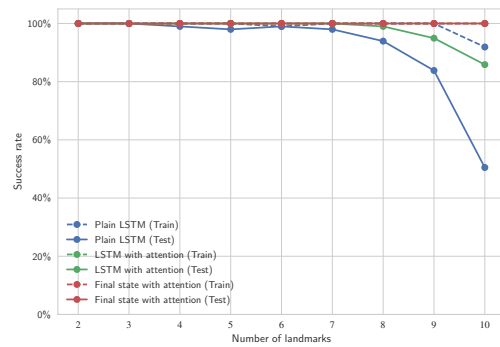


Figure 8. Success rates of different architectures for particle reaching. The “Train” curves show the success rates when conditioned on demonstrations seen during training, and running the policy on initial conditions seen during training, while the “Test” curves show the success rates when conditioned on new trajectories and operating in new situations. Both attention-based architectures achieve perfect training success rates, and the curves are overlapped.

However, the same conclusion does not appear to hold as the task becomes more complicated, as the next set of experiments shows.

5.2. Block Stacking

The particle reaching tasks nicely demonstrates the challenges in generalization in a simplistic scenario. However, the tasks do not share a compositional structure, making the evaluation of generalization to new tasks challenging. The skills and the information content required for each individual task are also simple. Hence, we conduct fur-

ther experiments with the block stacking tasks described in Section 3.2.2. These experiments are designed to answer the following questions:

- How does training with behavioral cloning compare with DAGGER, given that sufficient data can be collected offline?
- How does conditioning on the entire demonstration compare to conditioning on the final desired configuration, even when the final configuration has enough information to fully specify the task?
- How does conditioning on the entire demonstration compare to conditioning on a “snapshot” of the trajectory, which is a small subset of frames that are most informative?
- Can our framework successfully generalize to types of tasks that it has never seen during training?
- What are the current limitations of the method?

To answer these questions, we compare the performance of the following architectures:

- **DAGGER:** We use the architecture described in Section 4.2, and train the policy using DAGGER.
- **BC:** We use the same architecture as previous, but train the policy using behavioral cloning.
- **Final state:** This architecture conditions on the final state rather than on the entire demonstration trajectory. For the block stacking task family, the final state uniquely identifies the task, and there is no need for additional information. However, a full trajectory, one which contains information about intermediate stages of the task’s solution, can make it easier to train the optimal policy, because it could learn to rely on the demonstration directly, without needing to memorize the intermediate steps into its parameters. This is related to the way in which reward shaping can significantly affect performance in reinforcement learning (Ng et al., 1999). A comparison between the two conditioning strategies will tell us whether this hypothesis is valid. We train this policy using DAGGER.
- **Snapshot:** This architecture conditions on a “snapshot” of the trajectory, which includes the last frame of each stage along the demonstration trajectory. This assumes that a segmentation of the demonstration into multiple stages is available at test time, which gives it an unfair advantage compared to the other conditioning strategies. Hence, it may perform better than

conditioning on the full trajectory, and serves as a reference, to inform us whether the policy conditioned on the entire trajectory can perform as well as if the demonstration is clearly segmented. Again, we train this policy using DAGGER.

We evaluate the policy on tasks seen during training, as well as tasks unseen during training. Note that generalization is evaluated at multiple levels: the learned policy not only needs to generalize to new configurations and new demonstrations of tasks seen already, but also needs to generalize to new tasks. We also perform a thorough breakdown analysis of the failure scenarios as the difficulty of the task varies. Videos of our experiments are available at <http://bit.ly/one-shot-imitation>.

Concretely, we collect 140 training tasks, and 43 test tasks, each with a different desired layout of the blocks. The number of blocks in each task can vary between 2 and 10. We collect 1000 trajectories per task for training, and maintain a separate set of trajectories and initial configurations to be used for evaluation. Similar to the particle reaching task, we inject noise into the trajectory collection process. The trajectories are collected using a hard-coded policy.

5.2.1. PERFORMANCE EVALUATION

Fig. 9 shows the performance of various architectures. Results for training and test tasks are presented separately, where we group tasks by the number of stages required to complete them. This is because tasks that require more stages to complete are typically more challenging. In fact, even our scripted policy frequently fails on the hardest tasks. We measure success rate per task by executing the greedy policy (taking the most confident action at every time step) in 100 different configurations, each conditioned on a different demonstration unseen during training. We report the average success rate over all tasks within the same group. Note that there are no tasks with 8 stages in the training tasks, and no tasks with 1 or 3 stages in the test tasks, and hence the corresponding entries are omitted.

From the figure, we can observe that for the easier tasks with fewer stages, all of the different conditioning strategies perform equally well and almost perfectly. As the difficulty (number of stages) increases, however, conditioning on the entire demonstration starts to outperform conditioning on the final state. One possible explanation is that when conditioned only on the final state, the policy may struggle about which block it should stack first, a piece of information that is readily accessible from demonstration, which not only communicates the task, but also provides valuable information to help accomplish it.

More surprisingly, conditioning on the entire demonstration also seems to outperform conditioning on the snapshot,

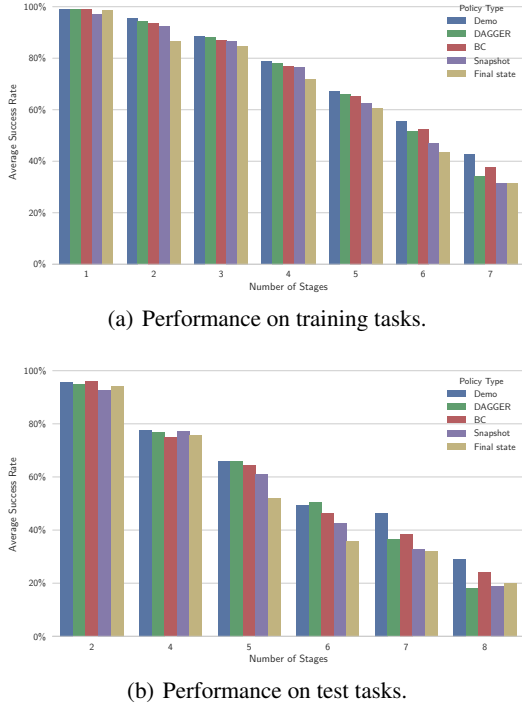


Figure 9. Comparison of different conditioning strategies. The darkest bar shows the performance of the hard-coded policy, which unsurprisingly performs the best most of the time. For architectures that use temporal dropout, we use an ensemble of 10 different downsampled demonstrations and average the action distributions. Then for all architectures we use the greedy action for evaluation.

which we originally expected to perform the best. We suspect that this is due to the regularization effect introduced by temporal dropout, which effectively augments the set of demonstrations seen by the policy during training.

Another surprising finding was that training with behavioral cloning has the same level of performance as training with DAGGER, which suggests that the entire training procedure could work without requiring interactive supervision. In our preliminary experiments, we found that injecting noise into the trajectory collection process was important for behavioral cloning to work well, hence in all experiments reported here we use noise injection.³ In practice, such noise can come from natural human-induced noise through tele-operation, or by artificially injecting additional noise before applying it on the physical robot.

Unless otherwise mentioned, all subsequent experiments

³Specifically, for each trajectory, we sample a scaling factor uniformly from $\{0, 0.001, 0.01\}$, and before computing the next world state, we add standard Gaussian noise to the actions rescaled by this scaling factor.

are conducted with the architecture conditioned on full demonstrations, and trained using DAGGER.

5.2.2. EVALUATING PERMUTATION INVARIANCE

During training and in the previous evaluations, we only select one task per equivalence class, where two tasks are considered equivalent if they are the same up to permuting different blocks. This is based on the assumption that our architecture is invariant to permutations among different blocks. For example, if the policy is only trained on the task `abcd`, it should perform well on task `dcbac`, given a single demonstration of the task `dcbac`. We now experimentally verify this property by fixing a training task, and evaluating the policy’s performance under all equivalent permutations of it. As Fig. 10 shows, although the policy has only seen the task `abcd`, it achieves the same level of performance on all other equivalent tasks.

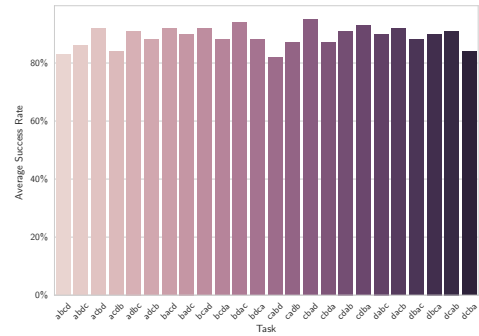


Figure 10. Performance of policy on a set of tasks equivalent up to permutations.

5.2.3. EFFECT OF ENSEMBLING

We now evaluate the importance of sampling multiple downsampled demonstrations during evaluation, which was introduced in Section 4.2.2. Fig. 11 shows the performance across all training and test tasks, as the number of ensembles varies from 1 to 20. We observe that more ensembles helps the most for tasks with fewer stages. On the other hand, it consistently improves performance for the harder tasks, although the gap is smaller. We suspect that this is because the policy has learned to attend to frames in the demonstration trajectory where the blocks are already stacked together. In tasks with only 1 stage, for example, it is very easy for these frames to be dropped in a single downsampled demonstration. On the other hand, in tasks with more stages, it becomes more resilient to missing frames. Using more than 10 ensembles appears to provide no significant improvements, and hence we used 10 ensembles in our main evaluation.

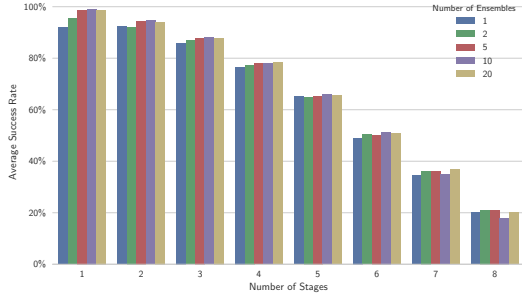


Figure 11. Performance of various number of ensembles.

5.2.4. BREAKDOWN OF FAILURE CASES

To understand the limitations of the current approach, we perform a breakdown analysis of the failure cases. We consider three failure scenarios: “Wrong move” means that the policy has arranged a layout incompatible with the desired layout. This could be because the policy has misinterpreted the demonstration, or due to an accidental bad move that happens to scramble the blocks into the wrong layout. “Manipulation failure” means that the policy has made an irrecoverable failure, for example if the block is shaken off the table, which the current hard-coded policy does not know how to handle. “Recoverable failure” means that the policy runs out of time before finishing the task, which may be due to an accidental failure during the operation that would have been recoverable given more time. As shown in Fig. 12, conditioning on only the final state makes more wrong moves compared to other architectures. Apart from that, most of the failure cases are actually due to manipulation failures that are mostly irrecoverable.⁴ This suggests that better manipulation skills need to be acquired to make the learned one-shot policy more reliable.

5.2.5. VISUALIZATION

Finally, we visualize the attention mechanisms underlying the main policy architecture. There are two kinds of attention we are mainly interested in, one where the policy attends to different time steps in the demonstration, and the other where the policy attends to different blocks in the current step, to filter out irrelevant signals. Fig. 13 shows a subset of the attention heatmaps, and the full set of visualizations, together with key frames of the neural network

⁴Note that the actual ratio of misinterpreted demonstrations may be different, since the runs that have caused a manipulation failure could later lead to a wrong move, were it successfully executed. On the other hand, by visually inspecting the videos, we observed that most of the trajectories categorized as “Wrong Move” are actually due to manipulation failures (except for policy conditioning on the final state, which does seem to occasionally execute an actual wrong move).

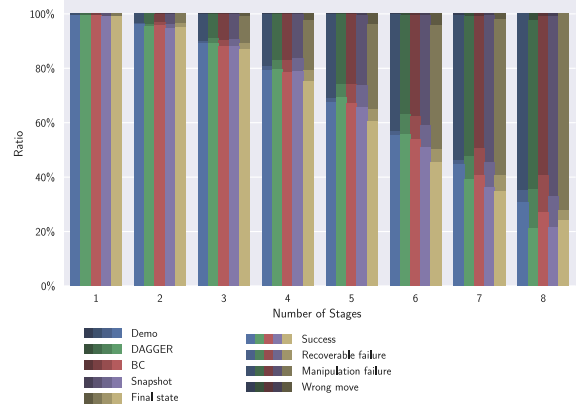


Figure 12. Breakdown of the success and failure scenarios. The area that each color occupies represent the ratio of the corresponding scenario.

policy executing the task, can be found in Appendix B.3.

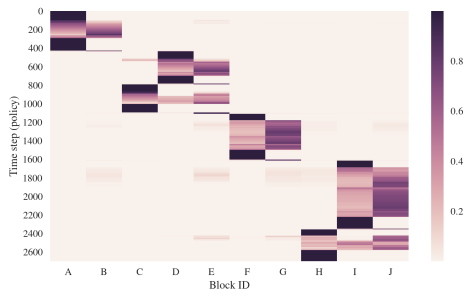
In Fig. 13(a), we can observe that the policy almost always focuses on a small subset of the block positions in the current state, which allows the manipulation network to generalize to operations over different blocks.

In Fig. 13(b), we can observe a sparse pattern of time steps that have high attention weights. This suggests that the policy has essentially learned to segment the demonstrations, and only attend to important key frames. Note that there are roughly 6 regions of high attention weights, which nicely corresponds to the 6 stages required to complete the task.

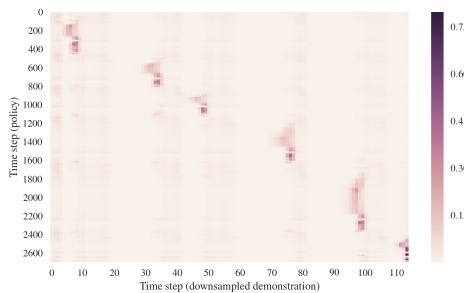
6. Conclusions

In this work, we presented a simple model that maps a single successful demonstration of a task to an effective policy that solves said task in a new situation. We demonstrated effectiveness of this approach on two domains, particle reaching and block stacking. There are a lot of exciting directions for future work. We plan to extend the framework to demonstrations in the form of image data, which will allow more end-to-end learning without requiring a separate perception module. We are also interested in enabling the policy to condition on multiple demonstrations, in case where one demonstration does not fully resolve ambiguity in the objective.⁵ Furthermore and most importantly, we hope to scale up our method on a much larger and broader distribution of tasks, and explore its potential towards a general robotics imitation learning system

⁵Many tasks involving abstract concepts fall into this category. For instance, in sorting and grouping different objects, whether the objective was to group objects based on color or based on shape.



(a) Attention over different blocks in the current state.



(b) Attention over downsampled demonstration.

Figure 13. Visualizing attentions performed by the policy during an entire execution. The task being performed is `ab cde fg hij`. Note that the policy has multiple query heads for each type of attention, and only one query head per type is visualized.

that would be able to achieve an overwhelming variety of tasks.

7. Acknowledgements

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A. More Details on Particle Reaching

A.1. Learning Curves

Fig. 14 shows the learning curves for the three architectures designed for the particle reaching tasks, as the number of landmarks is varied, by running the policies over 100 different configurations, and computing success rates over both training and test data. We can clearly observe that both LSTM-based architectures exhibit overfitting as the number of landmarks increases. On the other hand, using attention clearly improves generalization performance, and when conditioning on only the final state, it achieves perfect generalization in all scenarios. It is also interesting to observe that learning undergoes a phase transition. Intuitively, this may be when the network is learning to infer the task from the demonstration. Once this is finished, the learning of control policy is almost trivial.

A.2. Exact Performance Numbers

Table 1 and Table 2 show the exact performance numbers for reference.

#Landmarks	Plain LSTM	LSTM with attention	Final state with attention
2	100.0%	100.0%	100.0%
3	100.0%	100.0%	100.0%
4	100.0%	100.0%	100.0%
5	100.0%	100.0%	100.0%
6	99.0%	100.0%	100.0%
7	100.0%	100.0%	100.0%
8	100.0%	100.0%	100.0%
9	100.0%	100.0%	100.0%
10	91.9%	100.0%	100.0%

Table 1. Success rates of particle reaching conditioned on seen demonstrations, and running on seen initial configurations.

#Landmarks	Plain LSTM	LSTM with attention	Final state with attention
2	100.0%	100.0%	100.0%
3	100.0%	100.0%	100.0%
4	99.0%	100.0%	100.0%
5	98.0%	100.0%	100.0%
6	99.0%	100.0%	100.0%
7	98.0%	100.0%	100.0%
8	93.9%	99.0%	100.0%
9	83.8%	94.9%	100.0%
10	50.5%	85.9%	100.0%

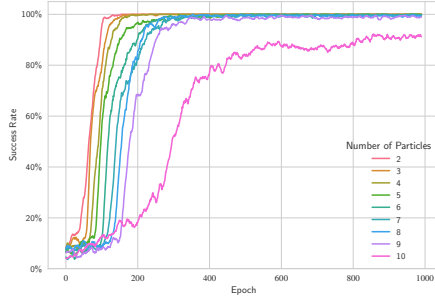
Table 2. Success rates of particle reaching conditioned on unseen demonstrations, and running on unseen initial configurations.

B. More Details on Block Stacking

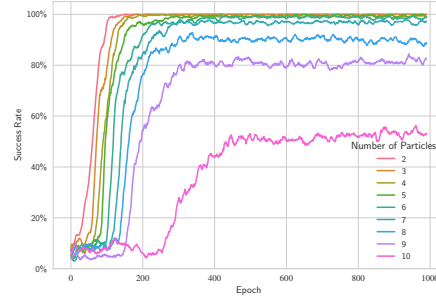
B.1. Learning Curves

Fig. 15 shows the learning curves for different architectures designed for the block stacking tasks. These learning curves do not reflect final performance: for each evaluation point, we sample tasks and demonstrations from training data, reset the environment to the starting point of some particular stage (so that some blocks are already stacked), and only run the policy for up to one stage. If the training algorithm is DAGGER, these sampled trajectories are annotated and added to the training set. Hence this evaluation does not evaluate generalization. We did not perform full evaluation as training proceeds, because it is very time consuming: each evaluation requires tens of thousands of trajectories across over > 100 tasks. However, these figures are still useful to reflect some relative trend.

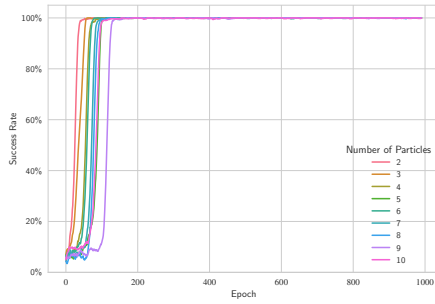
From these figures, we can observe that while conditioning on full trajectories gives the best performance which was shown in the main text, it requires much longer training time, simply because conditioning on the entire demonstration requires



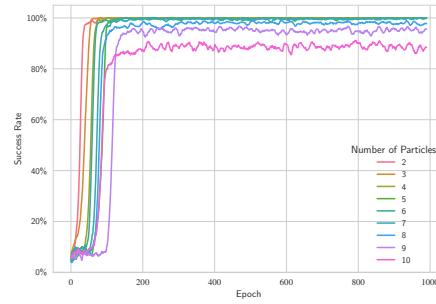
(a) Plain LSTM (Train)



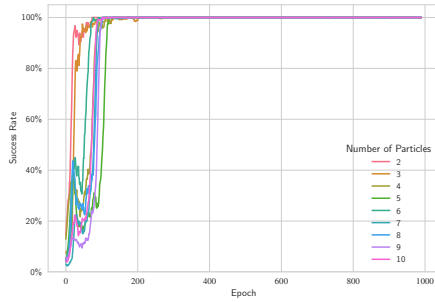
(b) Plain LSTM (Test)



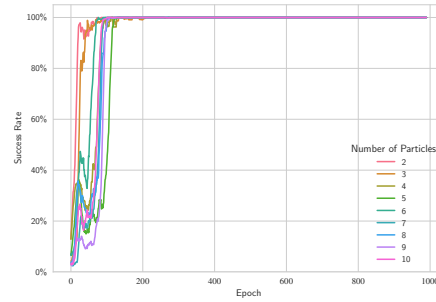
(c) LSTM with attention (Train)



(d) LSTM with attention (Test)



(e) Final state with attention (Train)

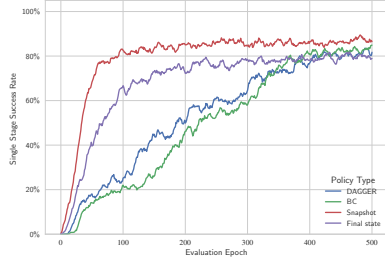


(f) Final state with attention (Test)

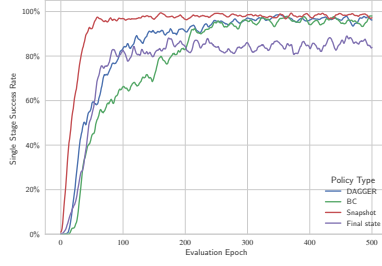
Figure 14. Learning curves for particle reaching tasks. Shown success rates are moving averages of past 10 epochs for smoother curves. Each policy is trained for up to 1000 epochs, which takes up to an hour using a Titan X Pascal GPU (as can be seen from the plot, most experiments can be finished sooner).

more computation. In addition, this may also be due to the high variance of the training process due to downsampling demonstrations, as well as the fact that the network needs to learn to properly segment the demonstration. It is also interesting that conditioning on snapshots seems to learn faster than conditioning on just the final state, which again suggests that conditioning on intermediate information is helpful, not only for the final policy, but also to facilitate training. We also observe that learning happens most rapidly for the initial stages, and much slower for the later stages, since manipulation becomes more challenging in the later stages. In addition, there are fewer tasks with more stages, and hence the later stages are not sampled as frequently as the earlier stages during evaluation.

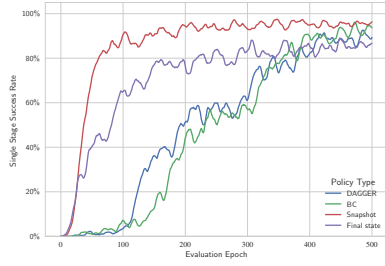
One-Shot Imitation Learning



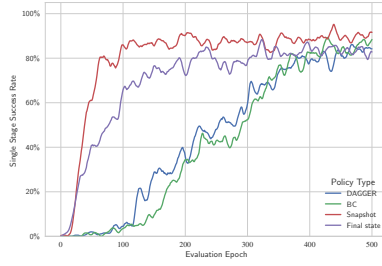
(a) All Stages



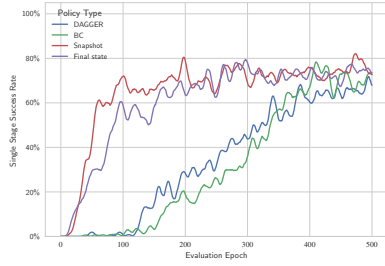
(b) Stage 0



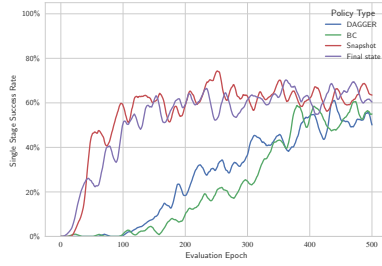
(c) Stage 1



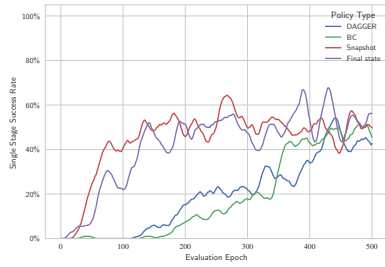
(d) Stage 2



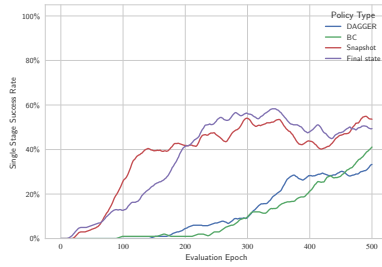
(e) Stage 3



(f) Stage 4



(g) Stage 5



(h) Stage 6

Figure 15. Learning curves of block stacking task. The first plot shows the average success rates over initial configurations of all stages. The subsequent figures shows the breakdown of each stage. For instance, “Stage 3” means that the first 3 stacking operations are already completed, and the policy is evaluated on its ability to perform the 4th stacking operation.

B.2. Exact Performance Numbers

Exact performance numbers are presented for reference:

- Table 3 and Table 4 show the success rates of different architectures on training and test tasks, respectively;
- Table 5 shows the success rates across all tasks as the number of ensembles is varied;
- Table 6 shows the success rates of tasks that are equivalent to `abcd` up to permutations;
- Table 7, Table 8, Table 9, Table 10, and Table 11 show the breakdown of different success and failure scenarios for all considered architectures.

#Stages	Demo	DAGGER	BC	Snapshot	Final state
1	99.1%	99.1%	99.1%	97.2%	98.8%
2	95.6%	94.3%	93.7%	92.6%	86.7%
3	88.5%	88.0%	86.9%	86.7%	84.8%
4	78.6%	78.2%	76.7%	76.4%	71.9%
5	67.3%	65.9%	65.4%	62.5%	60.6%
6	55.7%	51.5%	52.4%	47.0%	43.6%
7	42.8%	34.3%	37.5%	31.4%	31.5%

Table 3. Success rates of different architectures on training tasks of block stacking.

#Stages	Demo	DAGGER	BC	Snapshot	Final state
2	95.8%	94.9%	95.9%	92.8%	94.1%
4	77.6%	77.0%	74.8%	77.2%	75.8%
5	65.9%	65.9%	64.3%	61.1%	51.9%
6	49.4%	50.6%	46.5%	42.6%	35.9%
7	46.5%	36.5%	38.5%	32.8%	32.0%
8	29.0%	18.0%	24.0%	19.0%	20.0%

Table 4. Success rates of different architectures on test tasks of block stacking.

#Stages	1 Ens.	2 Ens.	5 Ens.	10 Ens.	20 Ens.
1	91.9%	95.4%	98.8%	99.1%	98.7%
2	92.3%	92.2%	94.5%	94.6%	94.1%
3	86.0%	86.8%	87.9%	88.0%	87.9%
4	76.6%	77.4%	77.9%	78.0%	78.3%
5	65.1%	65.0%	65.3%	65.9%	65.5%
6	49.0%	50.4%	50.1%	51.3%	50.8%
7	34.4%	36.1%	36.0%	34.9%	36.8%
8	20.0%	21.0%	21.0%	18.0%	20.0%

Table 5. Success rates of varying number of ensembles using the DAGGER policy conditioned on full trajectories, across both training and test tasks.

B.3. More Visualizations

Fig. 16 and Fig. 17 show the full set of heatmaps of attention weights. Interestingly, in Fig. 16, we observe that rather than attending to two blocks at a time, as we originally expected, the policy has learned to mostly attend to only one block at a time. This makes sense because during each of the grasping and the placing phase of a single stacking operation, the policy needs to only pay attention to the single block that the gripper should aim towards. For context, Fig. 18 and Fig. 19 show key frames of the neural network policy executing the task.

One-Shot Imitation Learning

Task ID	Success Rate
abcd	83.0%
abdc	86.0%
acbd	92.0%
acdb	84.0%
adbc	91.0%
adcb	88.0%
bacd	92.0%
badc	90.0%
bcad	92.0%
bcda	88.0%
bdac	94.0%
bdca	88.0%
cabd	82.0%
cadb	87.0%
cbad	95.0%
cbda	87.0%
cdab	91.0%
cdba	93.0%
dabc	90.0%
dacb	92.0%
dbac	88.0%
dbca	90.0%
dcab	91.0%
dcba	84.0%

Table 6. Success rates of a set of tasks that are equivalent up to permutations, using the DAGGER policy conditioned on full trajectories.

#Stages	Success	Recoverable failure	Manipulation failure	Wrong move
1	99.3%	0.0%	0.7%	0.0%
2	95.9%	0.4%	3.7%	0.0%
3	89.1%	0.7%	10.1%	0.1%
4	79.2%	1.2%	19.4%	0.1%
5	67.5%	1.4%	30.9%	0.2%
6	55.2%	1.4%	43.1%	0.3%
7	44.6%	1.7%	53.2%	0.6%
8	30.9%	4.3%	64.9%	0.0%

Table 7. Breakdown of success and failure scenarios for Demo policy.

#Stages	Success	Recoverable failure	Manipulation failure	Wrong move
1	99.4%	0.0%	0.6%	0.0%
2	95.3%	0.9%	3.8%	0.0%
3	89.1%	1.9%	8.8%	0.1%
4	79.5%	3.5%	16.7%	0.3%
5	69.1%	5.0%	25.6%	0.3%
6	55.8%	7.3%	36.4%	0.5%
7	39.0%	8.6%	51.5%	0.8%
8	21.2%	14.1%	62.4%	2.4%

Table 8. Breakdown of success and failure scenarios for DAGGER policy.

One-Shot Imitation Learning

#Stages	Success	Recoverable failure	Manipulation failure	Wrong move
1	99.6%	0.0%	0.4%	0.0%
2	95.6%	1.1%	3.2%	0.1%
3	88.1%	2.2%	9.5%	0.2%
4	78.5%	4.5%	16.8%	0.2%
5	67.2%	6.6%	25.7%	0.4%
6	53.9%	8.3%	37.1%	0.6%
7	40.6%	9.8%	48.7%	0.9%
8	27.0%	13.5%	58.4%	1.1%

Table 9. Breakdown of success and failure scenarios for BC policy.

#Stages	Success	Recoverable failure	Manipulation failure	Wrong move
1	99.1%	0.0%	0.9%	0.0%
2	94.5%	1.6%	3.8%	0.1%
3	88.0%	2.5%	9.3%	0.2%
4	78.9%	4.6%	16.2%	0.3%
5	65.6%	8.0%	25.8%	0.6%
6	50.8%	8.3%	40.2%	0.7%
7	36.1%	9.2%	54.2%	0.4%
8	21.6%	11.4%	65.9%	1.1%

Table 10. Breakdown of success and failure scenarios for Snapshot policy.

#Stages	Success	Recoverable failure	Manipulation failure	Wrong move
1	99.2%	0.0%	0.8%	0.0%
2	95.1%	1.3%	3.6%	0.0%
3	86.7%	2.5%	9.7%	1.1%
4	75.2%	4.0%	18.3%	2.5%
5	60.5%	4.3%	31.2%	4.0%
6	45.5%	4.7%	45.5%	4.3%
7	34.9%	5.6%	57.3%	2.2%
8	24.1%	3.6%	72.3%	0.0%

Table 11. Breakdown of success and failure scenarios for Final state policy.

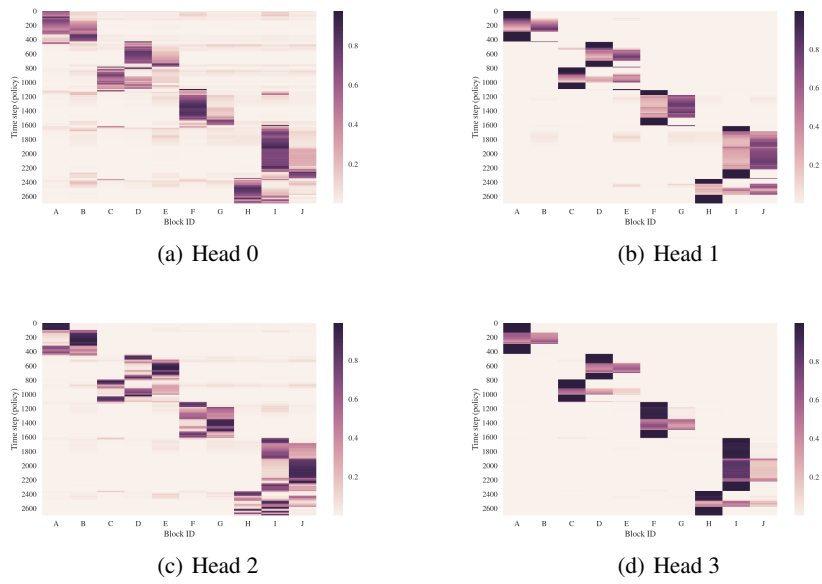


Figure 16. Heatmap of attention weights over different blocks of all 4 query heads.

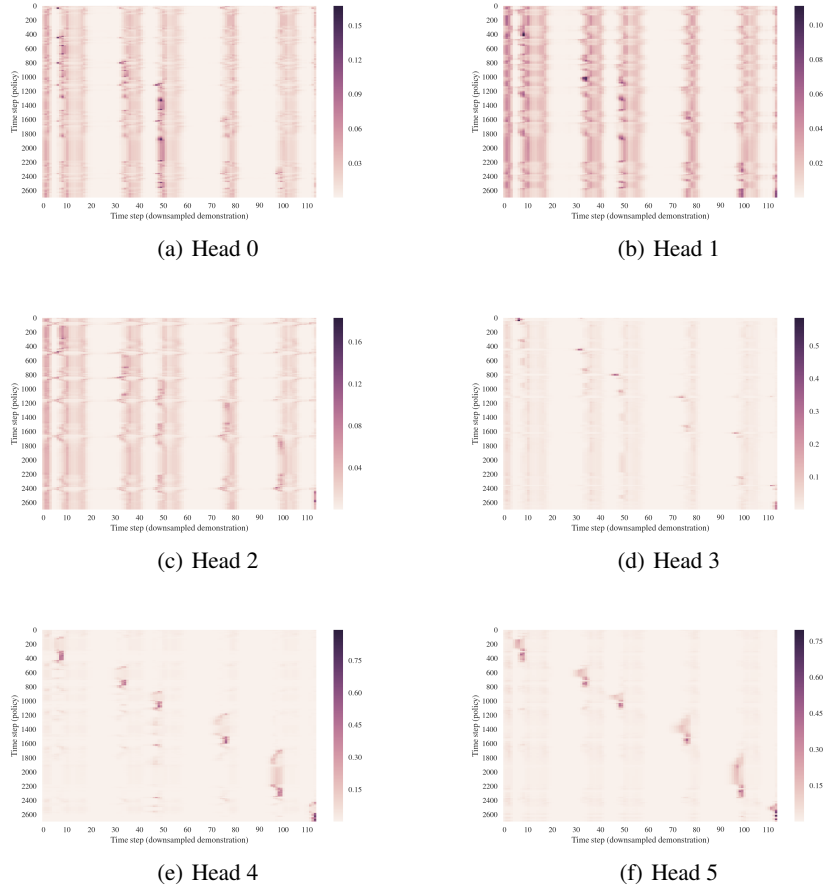


Figure 17. Heatmap of attention weights over downsampled demonstration trajectory of all 6 query heads. There are 2 query heads per step of LSTM, and 3 steps of LSTM are performed.

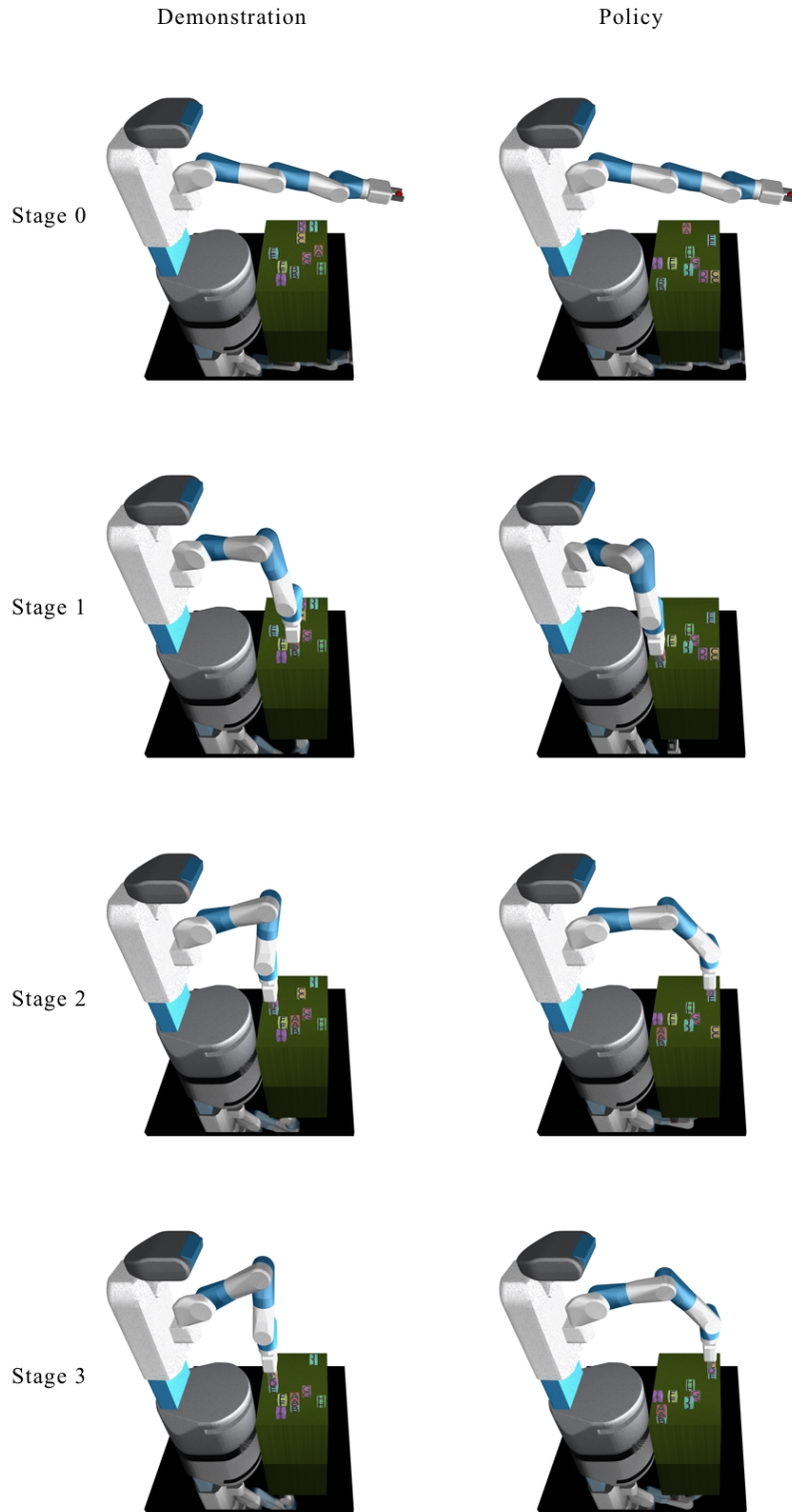


Figure 18. Illustration of the task used for the visualization of attention heatmaps (first half). The task is `ab cde fg hij`. The left side shows the key frames in the demonstration. The right side shows how, after seeing the entire demonstration, the policy reproduces the same layout in a new initialization of the same task.

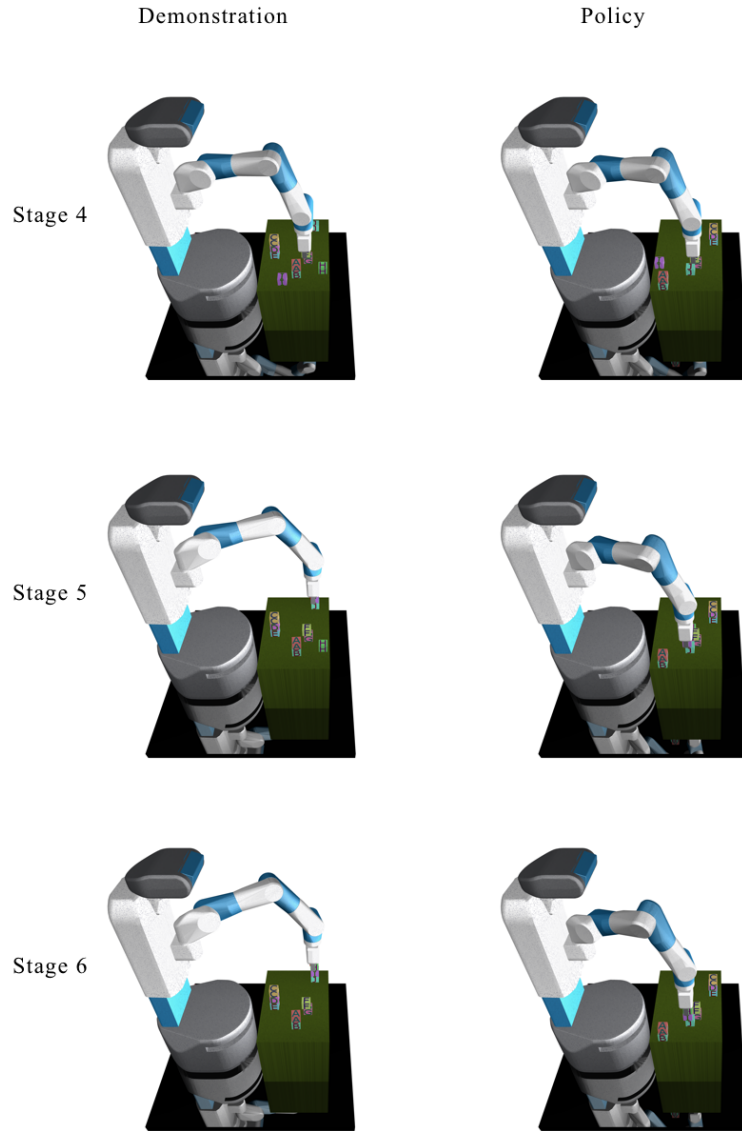


Figure 19. Illustration of the task used for the visualization of attention heatmaps (second half). The task is $ab \ cde \ fg \ hij$. The left side shows the key frames in the demonstration. The right side shows how, after seeing the entire demonstration, the policy reproduces the same layout in a new initialization of the same task.